Human Effects in Early Stage Construction Contract Price Forecasting

R. M. Skitmore, S. G. Stradling, and A. P. Tuohy

***Abstract*—This paper describes a postal survey of UK quantity surveyors to relate human factors, such as experience and personality, to conceptual estimating expertise. Composite variables were derived by factor analysis and examined against estimates of average national prices for several types of building. It is shown that expertise is very much of a project specific nature and does not extend in a simplistic way to projects outside the defined domain and that estimators must exercise of great caution when undertaking work even slightly outside their regular activities. Different building types demand different emphasis and special attention is drawn to the complexity of the project, the degree of services content, and particular sub-market conditions. The easiest projects to estimate appear to be industrial (factories) and residential (houses) with offices being the hardest, probably due to the wider variety of design and quality options in the latter. *Knowledge* and *care* are identified as the most crucial attributes of good estimators. A few myths are also dispelled. Geographical location, for instance, was found not to be a major issue. Similarly, there was no evidence of any "X" factor whereby individuals can claim any mystical inborn talent. The indications are that good estimators have exactly the same attributes as good gamblers—they do their research selectively and thoroughly, think carefully, and concentrate on what they know best.**

I. INTRODUCTION

ESTIMATES of construction contract value are frequently needed in the very early stages of the design of construction work in order to inform clients of their likely financial liability and report on the cost consequences of major design decisions. As the usual construction procurement arrangements effectively prohibit the involvement of the constructor until all the major design decisions have been made, forecasts have to be made by some member of the design team rather than constructors' estimators. Early stage forecasts are by their very nature rather imprecise. Indeed, as the forecasts to some extent always precede design decisions, they can be thought of as budgets or targets rather than forecasts of independent events. Nevertheless, early stage forecasts are needed and provided and their quality (accuracy) is judged by their closeness to the eventual lowest tender (bid).

Construction contract price forecasting practice is generally heavily dependent on the skill of the forecaster. This skill is associated with other factors affecting the quality of forecasts—the nature of the target, information, technique, and feedback—and the personal attributes of the forecaster himself combining to provide the general term of *expertise* [6].

Construction consultants (usually quantity surveyors, in the UK) have for a long time claimed superior abilities in construction price forecasting, with "intuitive adjustments" of detailed forecasts thought to account for a reduction of four percent in the coefficient of variation of errors [1, p. 12]. Research evidence in human effects in early stage construction price estimating, however, is rather limited as the main interest has, until recently, been concentrated on the informational aspects involved.

Jupp and McMillan [3], in the course of research into the effect of information on forecasting accuracy, found marked differences between the three individual subjects in their studies and, as the best performance came from the most senior of the subjects, it was concluded that the degree of experience must have been the main causal factor.

Morrison and Stevens (1980) also noticed differences between forecasting performance for different types of contracts, attributing the differences in performance to the different degree of forecasters' familiarity with the types involved.

Skitmore [5] found further evidence of significant individual performance differences between the twelve surveyors involved in his experimental study. This work examined the relationship between various experiential and personality characteristics of the subjects and measures of consistency (error variance), bias (mean error), and general accuracy (mean square error) in contract price forecasting, concluding that 1) subjects with high recall abilities, self-claimed expertise, low mental imagery of the physical characteristics of the building, and high general and specific contract type forecasting experience were the most consistent forecasters, 2) self-claimed experts produced the lowest forecasts, 3) subjects with high recall abilities, high mental imagery, and contract experience produced the highest forecasts, and 4) subjects who were more relaxed and confident, and more concerned with maintaining familiarity with the market and overall price levels than the routine collection and careful analysis of detailed information, were generally the most accurate.

This paper describes a further, large-scale, study of human aspects of construction price forecasting performance by quantity surveyors, executed by means of a postal questionnaire. All references to previous work are, unless otherwise stated, to [5].

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II. The Questionnaire

A comprehensive questionnaire was developed to supplement and extend previous findings. The final questionnaire was eight pages long, took between twenty and thirty minutes to complete, and was divided into four sections: 1) experience profile, 2) expertise, 3) "ball-park" forecasts, and 4) personality inventory.

These component parts were designed to, variously, yield information on the general and specific job experience of respondents and their claimed expertise in particular areas, their views on factors considered germane to forecasting expertise, their "baseline" estimate in pounds per square meter floor area of five common types of buildings (office buildings, for example, might be thought to be generally £650 per square meter of gross floor area while a figure of £400 might be considered to be more appropriate for industrial buildings generally), and their views on the psychological characteristics that they and an ideal forecaster ought to possess. The main interest was to consider the relationship between the accuracy of early stage forecasts in terms of the difference between the baseline estimates and average regionally adjusted prices, and experience, expertise, and personality of the forecaster.

A. Experience Profile

This section asked for age (the mean was 44 years), length of service in the profession (mean 25 years) and qualifications obtained.

In a number of recent studies, variables such as these have been found both to covary with each other and to give some purchase on the forecasting performance variables of interest. For example, it has been shown that lower age is significantly associated with greater stress in the police service even when sex, rank, and length of service effects are controlled and despite a high level of multicollinearity among the set of predictor variables; and that the level of education significantly differentiates two groups of police officers with demonstrably different approaches to their role [7]. However, neither age, service, nor type of qualification gave any appreciable purchase upon the variables of interest here.

Specific job experience and claimed expertise at forecasting the likely cost of a generic class of building contracts were implicated previously as important predictors of forecasting accuracy. Effort was therefore made in this phase of the investigation to obtain a much more detailed accounting of specific experience and rate current expertise. The five main contract types—schools, housing, offices, factories, and health centers—of the previous study were retained, but now divided down further into primary schools, secondary schools, and other educational; sheltered houses, speculative houses, and other residential; offices, shops, and other commercial; unit factories, warehouses, and other industrial; health centers, old people's homes, and other social/medical. Respondents were invited to indicate the number of each of these subcategories of contracts they had experienced over each of four five-year time periods from 1967 through 1986, and also to rate their current expertise at each of these contract types on a five-point scale between 1 (low) and 5 (high). By this method it was hoped to obtain a more detailed picture of the interplay between the two factors of specific experience and claimed expertise.

B. Views on Expertise and on Accuracy

In the previous study respondents' views on expertise, the definition of an expert forecaster, the skills required for successful forecasting, and the development of these skills were elicited by means of a semistructured interview. Common responses from this exploratory investigation were compiled and consolidated into closed-format rating scales for the postal questionnaire. A heterogeneous list of nineteen characteristics was compiled, covering a range of different kinds of attributes. These were arranged alphabetically from "ability to identify important aspects of contract" to "training at post-qualification stage" to avoid imposing any prior conceptual organization on the items. Respondents were asked to rate the importance of each item to expertise in forecasting. Respondents were also offered the facility of nominating additional factors and of rating their perceived importance on the same scale, but few did so.

The previous study suggested that variations in task factors made little difference to forecasting accuracy, with little consensus concerning the salience of different items of task information save for gross floor area. Believing that there really must be some aspects of the task, variation in which can produce systematic variation in forecasts of likely building price, it was decided to pursue this matter at a greater level of generality than previously, requesting rating of more overarching factors such as complexity of contract and site characteristics. Accordingly, a list of thirteen such factors was devised, randomly ordered and displayed for respondents with the request that they rate the importance of each on a five-point scale from 1 (low importance) to 5 (high importance) and that they do this both in general terms and separately for each of five specific contract types—primary school, sheltered housing, offices, unit factories, and health centers.

Opportunity was also taken within this section of the questionnaire to investigate respondents' perceptions of the effects of cost planning on prices and, concomitantly, the extent to which the presence or absence of cost planning was seen as affecting likely forecasting accuracy. *Cost planning* is the term used for a set of procedures aimed at advising designers on the likely implications of their work on the contract value. Importantly, cost planning should provide designers with continual cost evaluation feedback as the design evolves and therefore guide the design toward a budget or target. Ideally, cost planning should reduce early stage forecasts to the role of self-fulfilling prophesies. In reality, however, this is not quite the case but nevertheless we expect the accuracy of early stage forecasts to be better with cost planning than without cost planning.

Respondents were asked to indicate both in general and for the five generic building contracts—primary school, sheltered housing, offices, unit factories, and health center—what accuracy level they anticipated for forecasts with cost planning and, subsequently, for forecasts without cost planning.

C. Gross Cost Forecasts of Five Building Contracts

The previous investigation had found forecaster factors—such as claimed expertise—which appeared to covary with differences in accuracy quite independently of the number of items of task information selected or past contracts consulted. We now wished to investigate whether such influences would also be found in the absence of any additional pieces of task information. Accordingly, our respondents were requested to give "a quick 'ball-park' estimate" for each of the five generic building contracts provided only with the category of contract and the gross floor area. As a corrective against regional variations in building contract prices, respondents were advised to "assume that each is located in your own geographical area" and responses were subsequently corrected by dividing by the published regional factor applicable at that time [2]. This allowed straightforward comparisons between the responses of each subject with them all reduced to a common base. In addition, to ensure that all respondents were undertaking identical tasks, theywere further advised to "make each estimate at current prices, exclusive of fees, furniture and land." We could thus be reasonably certain that any variability between respondents was not due to some including and others omitting the costs associated with these factors.

Our previous investigations led us to belive that no one would feel it necessary to recourse to published guidelines on the values of ball-park estimates. This assumption was later confirmed in the analysis, where no two respondents provided the same estimates, even after adjusting for regional variations.

D. Actual and Ideal Personal Characteristics of Forecasters

It was of interest to determine whether any reliable relationship could be found between forecasting ability and indices of personality. The final part of the questionnaire was designed to metricate two aspects of this matter: first, how our respondents rated themselves on a number of standard personality dimensions, and second, whether there was any consensus among them over the personal characteristics which contributed to making accurate forecasts. For the first of these aims, the sixteen core dimensions of Cattell's 16PF personality inventory were used. However, the 16PF was too lengthy an instrument to include in full, and, in any case, many of the items of a personality inventory can be viewed as somewhat intrusive by those required to complete them. To overcome this problem, respondents were provided with sixteen bipolar scales from "Assertive . . . Accommodating" to "Undisciplined . . . Controlled" and a seven-point scale and invited to rate themselves for each contrast.

Respondents were also invited to consider ten personal traits or characteristics and to rate how important they felt each to be "for an ideal forecaster." They were again provided with a seven-point scale, this time ranging between two labeled endpoints, namely "Not important" and "Very important." A number of candidate traits were considered for inclusion in this instrument, the final list comprising Careful, Clever, Confident, Co-operative, Critical, Fast, Flexible, Knowledgeable, Pleasant, and Tough. These characteristics were taken as representing a number of factors known to be involved in gaining entry to the occupation of forecaster and in carrying out the business of forecasting for clients whether as part of a large concern or as sole principal of a small business.

Administration: Using information obtained from the Royal Institute of Chartered Surveyors (RICS) Quantity Surveying Division, a quota sample of recipients was drawn up ensuring that recipients were selected from all regions of England. A covering letter requested assistance with the research and asked that the questionnaire be completed by the member of staff in the organization who "most usually" undertook contract price forecasting. Approximately 700 questionnaires were distributed in late 1986. A number were returned uncompleted with explanations that while in membership of RICS, the firm or office engaged in one or more other aspects of chartered surveying practice but did not undertake forecasting work. A total of 82 completed returns were received from a wide spread of UK regions. The reasons for the low response rate is not known, but it is suspected that many potential respondents felt insufficiently qualified to claim themselves to be truly expert in the field, as quantity surveying involves many other activities in addition to precontract estimating. As a result, it was felt that those who did respond were likely to be very proficient in estimating and thus represent the characteristics and views of true experts in the field.

III. Results

The completed questionnaires gave rise to a considerable array of raw data, amounting to more than 200 variables in all. For the purposes of detailed analysis, the array was reduced wherever possible by generating factor scores, which were then systematically substituted for the original variables. These factor analyses were carried out by means of the program BMDP4M [8], using the available default options and adopting a VARIMAX rotation criterion throughout. As will be seen below, the factors thus obtained were on the whole quite readily interpretable; hence, the factor scores derived from them could be treated as the weighted composite scores of the relevant groups of variables.

The results presented here are organized into ten separate sections, beginning with detailed accounts of the findings obtained from each of the separate main items of the questionnaire and moving on to look in detail at the relationships between responses culled from different sections of the instrument. The ten sections are as follows:

Analysis 1: Distribution of forecasters' recent experience
Analysis 2: Self-rated expertise
Analysis 3: Characteristics contributing to expertise
Analysis 4: Rated importance of task elements
Analysis 5: Accuracy levels with and without cost planning
Analysis 6: Forecasts
Analysis 7: Personality inventory
Analysis 8: Trait attribution for an ideal forecaster
Analysis 9: Predictors of relative estimate size
Analysis 10: Predictors of estimate typicality

Analysis 1: Distribution of Forecaster's Recent Experience

The first of these data-reduction procedures was carried out on responses to the request that subjects "give us more detailed numbers for the different types of contract shown below." Fifteen contract types were given, and four 5-year time periods were specified (i.e., 1967–1971, 1972–1976, 1977–1981, and 1982–1986), but in order to ensure that all subjects were included, the factor analysis of these data was restricted to the most recent time period, namely 1982–1986. The subjects reported residential contracts as the most frequent type, accounting for an average of 28.5% of their recent experience. Commercial contracts were nearly as frequent, accounting for 26% of recent experience, while industrial and sociomedical contract types were intermediate at 21.3% and 16.0% respectively. Educational contracts were reported as the least frequent, accounting for only 8.1% of recent experience.

Inspection of the significant correlations occurring among the 15 recent experience variables showed a number of expected patterns (such as, for instance, a very high correlation between types of school), but also a number of interesting anomalies. For example, the subjects' reported experience in "other residential" contracts is highly correlated with experience in sheltered housing, but not in speculative housing. Similarly, "other sociomedical" contracts are correlated with health centers, but not with old people's homes. It may be, however, that some of these anomalies are derived from the generality or indeed the inappropriateness of the categories provided. On the other hand, it may be argued that the broad interpretability of the subsequent factor analysis suggests that these correlations do in fact access the pattern of co-occurrence of these various types of experience.

The factor analysis yielded 5 factors having eigenvalues greater than unity, accounting for 77.5% of the total variance. The factors (FA1 to FA5) were labeled with reference to the highest-loading variables; thus, FA1 was identified as primarily a commercial experience factor, although there were also substantial loadings derived from experience of speculative housing and old people's homes. Similarly, FA2 was seen as a public service factor, with high loadings on educational and sociomedical contract types. Interestingly, FA3 collected together the "other"—i.e., non-specific, contract types—and thus could be regarded as a versatility or general experience factor. FA4 was clearly recognizable as a "Residential experience factor" and FA5 as an industrial experience factor, neither having any substantial loadings inconsistent with these characterizations.

Standardized factor scores were generated, which were used as data in subsequent analyses, substituting for the fifteen separate recent-experience variables. Since the VARIMAX rotation criterion ensures the orthogonality of the factors, these factor scores were also orthogonal to one another. Thus, in subsequent analyses, the proportion of variance of any dependent variable which can be attributed to the effects of recent experience is simply expressed as the sum of its squared correlations with these five factor scores.

Analysis 2: Self-Rated Expertise

This analysis examined responses to the instruction "As objectively as possible, please assess your current level of expertise on each type of contract, on a scale between 1 (low) and 5 (high)." Mean ratings for the 15 contract types are set out in Table I, where it can be seen that the subjects reported the highest mean self-rated expertise for industrial and commercial contracts, and the lowest for educational contracts.The relationship between experience and self-rated expertise was explored by correlating subjective expertise with objective experience of each contract type in each of the four time periods (using only the 58 subjects whose experience covered the range). For all fifteen contract types the correlation between amount of experience and self-rated expertise was higher for the final time period (most recent quinquennium) than for each of the earlier time periods. However, the strength of association reported for the first time period was higher than that for the second on almost half of the contract types and higher than that found for the third period on a quarter. Fisher's r-to-z transformation was applied to the correlation coefficients giving 0.208, 0.190, 0.275, and 0.416 for the four time periods. The resulting z-scores were used as input to a one-way analysis of variance, with repeated measures across four levels of time, using the 15 contract types as cases. By this means the relationship between subjective expertise and objective experience was found to vary significantly across time ($F = 9.878$; $df = 3.56$; $p < 0.0001$). The positive linear trend across the four group means was found to be significant ($t = 4.855$, $p < 0.0001$), indicating that the strength of this relationship increased across time. However, there was also a significant quadratic trend component ($t = 4.500$, $p < 0.0001$), indicating that the cell mean for the first time period was significantly higher than the linear trend would predict, and hence that these date were better fitted by a U-shaped or J-shaped function. It was concluded that in addition to the tendency for the expertise/experience relationship to increase with recency, a primacy effect had also been observed.

The self-rated expertise scores for the fifteen contract types were then factor-analyzed, and 5 factors emerged with eigenvalues greater than 1 (FB1 to FB5), accounting for 75.0% of the total variance. As before, the factors were labeled in terms of their highest loadings, and it can be seen from Table I that the characterization was very clear-cut in this analysis. FB1 was labeled in terms of a dimension of commercial expertise, FB2 of industrial, FB3 of educational, FB4 of sociomedical, and FB5 of residential expertise, these being the dominant generic types of buildings selected for the study. This indicates that the respondents generally specialized in one of the five generic building types but with some extension into other types. Thus for instance, subjects specializing in producing estimates for commercial buildings also specialized to some extent in some (unspecified) industrial and educational buildings—indicating a more subtle range of experience than strictly building of a commercial nature. In order to capture this richer pattern of experience, the five sets of factor scores were generated, to replace the fifteen original variables in subsequent analyses.

Analysis 3: Characteristics Contributing to Expertise

The third analysis examined the rated importance (on a 5-point scale ranging from"not important" to "very important") of 19 items "which might be applied to expertise in the field

TABLE I
MEAN AND VARIMAX FACTOR ANALYSIS OF RATED CURRENT EXPERIENCE ON 15 CONTRACT TYPES, ACCOUNTING FOR 75% OF THE TOTAL VARIANCE (LOADINGS > 0.30 ARE SHOWN)

	Mean	SD	FB1	FB2	FB3	FB4	FB5
Other commercial	3.23	1.18	0.84				
Shops	3.20	1.21	0.74	0.31			
Offices	3.58	1.09	0.62	0.40			
Overall commercial	*3.34*	*0.97*					
Unit factories	3.30	1.39		0.91			
Warehouses	53.47	1.32		0.90			
Other industrial	3.31	1.30	0.44	0.46		0.35	
Overall industrial	*3.37*	*1.17*					
Secondary schools	1.84	1.08			0.90		
Primary schools	1.85	1.18			0.85		
Other educational	1.84	1.10	0.57		0.57		
Overall educational	*1.84*	*0.95*					
Other sociomedical	3.04	1.44				0.89	
Health centers	2.52	1.53				0.78	
Old people's homes	2.61	1.39				0.65	0.36
Overall sociomedical	*2.72*	*1.25*					
Speculative housing	2.91	1.38					0.80
Sheltered housing	3.37	1.44		0.31			0.79
Other residential	3.20	1.24					0.76
Overall residential	*3.17*	*1.10*					
Eigenvalues			*2.38*	*2.31*	*2.19*	*2.19*	*2.16*

TABLE II
MEAN AND VARIMAX FACTOR ANALYSIS OF RATED IMPORTANCE OF 19 CHARACTERISTICS AS COMPONENTS OF EXPERTISE IN FORECASTING, ACCOUNTING FOR 69% OF THE TOTAL VARIANCE (LOADINGS > 0.30 ARE SHOWN)

	Mean	SD	FC1	FC2	FC3	FC4	FC5	FC6	FC7
Skills acquired practicing job	4.33	0.73	0.80						
Judgement and intuition	4.41	0.92	0.67						
Identify important job aspects	4.61	0.71	0.55			0.31	-0.40	0.34	
Knowledge of market conditions	4.33	0.83	0.54	0.46	0.32				
Analytical ability	3.94	1.11	0.45	0.30	0.33			0.34	
Memory of similar contracts	3.76	1.16		0.82					
Memory of current contract	3.69	1.21		0.76			-0.30		
Personality factors	2.33	1.08	-0.35	0.48				0.34	
Ability to visualise building	3.98	1.08	0.31	0.46					0.38
Postqualification	3.22	1.34			0.81				
Qualification training	2.49	1.44			0.74				
Considered expert by others	2.74	1.29				0.88			
Considered expert by self	2.63	1.37				0.79			
Prepared to take risks	2.37	1.26					0.82		
Aware of client's requirements	4.52	0.77			-0.42		-0.58		
Natural estimating aptitude	3.17	1.37		0.32	-0.36		0.51	0.33	
Handle insufficient information	4.51	0.80						0.75	
Logical and systematic approach	4.07	1.11						0.69	
Length of time in profession	3.21	1.21							0.90
Eigenvalues			*2.33*	*2.26*	*1.94*	*1.84*	*1.78*	*1.74*	*1.22*

of forecasting." These are shown in Table II, together with their mean ratings and standard deviations. Since a scale ranging from 1 (low) to 5 (high) was used, 14 of the 19 items were assigned mean ratings higher than the given neutral point, indicating that on the whole this array of possible characteristics was seen as highly relevant by the subjects.

The ordered items arranged on this scale of importance provides an interesting picture of the subjects' own concept of expertise. The highest-scoring items seem in general to be those concerned with judgment, i.e., with fuzzy or indeterminate data, and these items precede those which deal with precision, logic and memory for details. Least important of all are items which might suggest that individual difference have a bearing on expert performance which does not derive from the actual practice of the job. Thus, personality factors, formal qualifications, attributions, and natural aptitude are all ranked relatively low. The sole inconsistent item at this end of the scale is risk-taking, which might be assumed to be an integral part of judgmental decisionmaking. However, this item may have been read as a personality variable rather than as an aspect of dealing with uncertain information, and so attracted low importance ratings.

None of the correlations among these items was particularly high, and indeed only four item-pairs were found to share more than 25% of their variance. These were the natural conjunctions between the two attributional items ("considered

TABLE III
MEAN AND VARIMAX FACTOR ANALYSIS OF RATED GENERAL IMPORTANCE OF 13 TASK ELEMENTS, ACCOUNTING FOR 70% OF THE TOTAL VARIANCE (LOADINGS > 0.30 ARE SHOWN)

Mean	SD	FD1	FD2	FD3	FD4	FD5	
Designers	3.68	1.15	0.81				
Complexity	3.93	1.05	0.79				
Services	3.86	1.06	0.73				
Site characteristics	3.61	1.16	0.56	0.46		-0.32	0.32
Market conditions	3.82	1.06		0.84			
Geographical location	3.06	1.11		0.75			
Time, penalties	2.69	1.33		0.56		0.37	
Quality	3.80	1.12		0.47	0.30	0.44	
Size of building	3.43	1.54			0.90		
Number of storeys	2.94	1.43			0.74	0.41	
BCIS files	2.39	1.18				0.80	
Cost limits	3.58	1.41					0.78
The client	3.35	1.34					0.67
Eigenvalues			*0.29*	*2.12*	*1.82*	*1.43*	*1.40*

by self" and "considered by others to be an expert"), between the two memory items ("for details of similar contracts" and "for details of current contract"), and the two training items ("qualifications" and "training at post-qualification stage"). The fourth was between "memory for details of similar contracts" and the "ability to visualise the finished building." Other relatively strong relationships were found between "judgment and intuition" and "skills acquired in practicing the job," and between "analytical ability" and "knowledge of market conditions." These data were then factor-analyzed, and the results are shown in Table II. Seven factors emerged (FC1 to FC7), accounting for 69% of the total variance. The largest factor (FC1) was interpreted as dealing with the subjects' own concept of professional competence; thus, there are major loadings on practical skills, judgment, the ability to seize on important aspects of an indeterminate database, etc. FC2, interestingly, consolidates those items which bear on psychological aspects, e.g., memory, personality, visual ability. For their highest loadings, FC3 was labeled as a training factor and FC4 as an attributional factor.

The largest loading on FC5 was risk-taking, with a subsidiary loading on natural aptitude, and negative loadings on client's requirements, identification of important aspects, and memory for details of the current contract. This pattern was considered to express an opposition between improvisational skills and the constraints of factual aspects of the contract, and FC5 was accordingly characterized in terms of risk acceptance factor. FC6 carried high loadings on dealing with insufficient information and using a logical and systematic approach, which were seen as two aspects of data processing skills. The last factor (FC7) was labeled as a length of service factor. The seven sets of factor scores were then generated, to replace the nineteen original variables in subsequent analyses.

Analysis 4: Rated Importance of Task Elements

Subjects were presented with a list of 13 task elements, and were asked to judge their importance on a scale of 1 (low) to 5 (high), firstly in general terms, and then for the 5 contract types separately. The mean general importance ratings are set out in Table III.

As before, the correlations were generally quite small, indicating that only four element pairs shared more than 25% of their variance ("geographical location" with "site characteristics" and "market conditions," "size of building" with "numberof stories," and "designers" with "site characteristics").

When these general ratings were factor-analyzed, five factors emerged (FD1 to FD5), accounting for 70% of the total variance (see Table III). Factor FD1, with high positive loadings from "designers," "complexity," "site characteristics," and "services," was designated as task complexity factor. FD2, with high loadings from "market conditions," "geographical location," and "time/penalties," and with moderate loadings from "quality" and "site characteristics," was labeled local conditions factor. FD3 was clearly a scale of contract factor, and FD4 referred to the use of records factor. Finally, FD5, with high loadings from "cost limits" and "the client," was seen as dealing with budget restrictions factor. Factor scores were generated, and filed under these descriptive terms.

The importance ratings specified to the 5 different contract types for these same 13 elements were now analyzed. Table IV sets out the rank order of the elements for each contract type. Kendall's coefficient of concordance was calculated twice for the rankings shown in Table IV, firstly excluding the general rating ($\underline{W}$ =0.751, $p < 0.001$), and secondly including it ($\underline{W} = 0.766$, $p < 0.001$). These results indicated that there was significant variation in the rank order of rated importance of these task elements across contract types.

The contract type ratings Project type ratings (excluding the general ratings) were then factor-analyzed, and fourteen significant factors emerged, accounting for 87.8% of the total variance. The first 13 of these dimensions corresponded precisely to the 13 task elements. It was therefore assumed that factor scores generated on these dimensions would merely create an alternative to the set of general importance ratings already obtained on the 13 task elements and already subjected to factor analysis. Moreover these factor scores would not be susceptible to higher-order factor analysis, since varimax factors are orthogonal. It was therefore anticipated that the original task element data were best represented by the general importance factor scores (but see Analysis 9 below).

TABLE IV
RANK ORDER OF MEAN RATED IMPORTANCE OF 13 TASK ELEMENTS, FOR 5 CONTRACT TYPES

	Gen	Sch	Hse	Off	Fac	Cen
Complexity	1	4	4	4.5	7	3
Services	2	5	6	2	6	1
Market conditions	3	2	2	3	1	4
Quality	4	6.5	7	1	5	5
Designers	5	6.5	5	4.5	9	7
Site characteristics	6	3	3	7	2	6
Cost limits	7	1	1	10	8	2
Size of building	8	8	8	8	3.5	9
The client	9	10	9	6	3.5	8
Geographical location	10	9	10	11	10	10
Number of storeys	11	13	11	9	13	11
Time, penalties	12	12	12	12	11	12
BCIS files	13	11	13	13	12	13

TABLE V
MEAN PERCENTAGE EXPECTED ACCURACY LEVELS FOR FORECASTING

		GEN	Sch	Hse	Off	Fac	Cen
with cost planning	M%	7.26	6.46	6.10	7.05	5.91	7.54
	SD	3.03	2.84	2.89	3.19	3.05	3.52
without cost planning	M%	11.63	10.05	10.17	11.28	10.18	11.39
	SD	4.39	4.13	4.13	4.41	4.39	4.16

Analysis 5: Accuracy Levels With and Without Cost Planning

Subjects were asked to judge "the expected accuracy levels, on average, for forecasts" with and without cost planning, both in general and for the 5 specific contract types. The means and standard deviations of the subjects' expected percentage accuracy levels (difference between estimate and lowest bid) are given in Table V. The data for the 5 specific contract types were subjected to an analysis of variance with repeated measures on two factors (cost vs. no cost planning, and 5 levels of contract type). Significant main effects were found of both planning ($\underline{F}$ = 166.36; df = 1, 77; $p < 0.0001$) and contract type ($\underline{F}$ = 6.61; df = 4.308; $p < 0.0001$), with no significant interaction ($\underline{F} < 1$). Thus, forecasts on some contract types are expected to be significantly less accurate than those on other contract types, whether with or without cost planning.

The correlations for the judgments with and without cost planning revealed that all but one were significant at the p< 0.05 criterion level. The accuracy ratings for the 5 contract types were then factor-analyzed, separately for the cost planning and no cost planning responses. In both cases a single factor emerged, with high positive loadings from all five contract types.

Analysis 6: Forecasts

Subjects were asked to give a "quick 'ball-park' estimate" for the five contract types. They were instructed to "assume that each is located in your own geographical area," and to make each estimate "at current prices, exclusive of fees, furniture, and land."

A number of transformations were now applied to the raw forecasts.The scores were first divided by the given gross floor area of each contract type, to yield cost per square meter. They were then standardized for month of estimate, using the national average prices for February to June 1987. Each datum was multiplied by the ratio of the appropriate value for June and the appropriate value for the month in which that particular questionnaire was returned, thus adjusting the whole database to the level of June 1987 prices. A further adjustment was then made to take account of geographical variation in prices, and each datum was divided by an appropriate regional coefficient.

The means, standard deviations, and coefficients of variation for the transformed forecasts are shown in Table VI. The relationship between the transformed forecasts and the national average prices for June 1987 was explored in two ways. Firstly, the proportional national average value was calculated by subtracting the national average price from the transformed forecast, and then dividing by the national average price. This calculation expressed the extent to which each estimate was greater than or smaller than the national average price for June 1987 for the relevant contract type. Secondly, the modulus (unsigned) proportional differences were calculated, to express the extent to which each estimate differed from the appropriate national value, regardless of the direction of the difference. The means and standard deviations for these signed and modulus differences are shown in Table VI.

The correlation matrix for the signed values produced significant positive values in all cases. The squared multiple correlation (SMC) of each of these variables with the other four is significant in all cases ($p < 0.001$). A composite measure of proportional estimate size was then obtained by factor-analyzing the five signed difference scores defined above. A single significant factor emerged, accounting for 51.7% of the variance.

Factor scores were generated and, since all five contract-specific signed difference variables yielded high positive loadings, these were assumed to index relative estimate size (factor FG1). The distribution of the factor scores was positively skewed.

Analysis 7: Personality Inventory

Subjects were presented with 16 bipolar trait-pairs with a seven-point scale extending between each pole. They were asked to tick the appropriate box on each scale to indicate where they thought their own personality fell between the two extremes. Table VII presents the mean ratings for each trait-pair. In each case, the scales were scored from 1 to 7 in the direction indicated. For items in the higher section of Table VII, therefore, the mean tends toward the right-hand trait, while for items in the lower section the tendency is toward the left-hand trait.

Factor analysis revealed six significant factors (FH1 to FH6), accounting for 63% of the total variance (Table VIII). Factor FH1, comprising high positive loadings on "secure," "venturesome," and "outgoing," and moderate negative loadings on "tender-minded" and "accommodating," was characterized as a confidence factor. Factor FH2, incorporating positive loadings on "conscientious," "tender-minded," "trusting," and "accommodating," was characterized as a compliance factor. Factor FH3 was labeled as nervousness factor, and factor FH4 as directness factor, in accordance with the highest loading traits in each case. FH5 was more difficult to

TABLE VI
MEAN FORECASTS, STANDARD DEVIATIONS, AND COEFFICIENTS OF VARIATION FOR 5 CONTRACT TYPES

	School	Houses	Offices	Factory	Health Center
Raw					
Mean	271360	780822	5791106	369132	231818
SD	47393	101735	1697527	84247	47778
CV	0.175	0.130	0.293	0.228	0.206
Pounds per Square Meter					
Mean	469.087	393.099	513.086	259.562	553.743
SD	90.021	53.008	122.612	64.258	117.779
CV	0.192	0.135	0.239	0.248	0.213
Difference for National Average (signed)					
Mean	-0.131	-0.057	-0.159	-0.089	-0.065
SD	0.167	0.127	0.201	0.225	0.199
Difference for National Average (modulus)					
Mean	0.177	0.113	0.216	0.202	0.164
SD	0.116	0.081	0.137	0.132	0.129

TABLE VII
MEAN RATING OF OWN PERSONALITY ON 16 BIPOLAR TRAITS, USING A 1-7 SCALE

Trait scored (1)	Mean	SD	Trait scored (7)
Undisciplined	5.63	1.12	Controlled
Less intelligent	5.44	0.80	More intelligent
Expedient	5.31	1.28	Conscientious
Group-orientated	5.28	1.49	Self-sufficient
Timid	5.10	0.91	Venturesome
Happy-go-lucky	4.99	1.16	Serious
Apprehensive	4.64	1.31	Secure
Imaginative	4.12	1.58	Practical
Assertive	4.05	1.30	Accommodating
Suspicious	3.74	1.35	Trusting
Outgoing	3.73	1.26	Reserved
Relaxed	3.63	1.34	Tense
Tough-minded	3.60	1.14	Tender minded
Shrewd	3.56	1.29	Forthright
Traditional	3.51	1.39	Radical
Calm	3.16	1.47	Emotional

recognize, incorporating positive loadings from "traditional," "self-sufficient," and "more intelligent," but a characterization of imperviousness factor was finally influenced. Factor FH6, with high positive loadings from "serious" and "controlled," could clearly be called a discipline factor. Factor scores were generated, and the resulting array was treated as an index to the subjects' model self concept oftheir own personalities.

Analysis 8: Trait Attribution for Ideal Early-Stage Forecaster

The final section of the questionnaire called for ratings on a seven-point scale of the importance of 10 personality traits for "an ideal early-stage forecaster." Table IX shows the mean rating and standard deviation for each trait.

Four factors emerged with eigenvalues greater than unity (FI1 to FI4), accounting for 62% of the total variance (see Table IX). Factor scores were generated, and those for factor FI1 (with high positive loadings from "cooperative," "careful," and "pleasant") were characterized as being helpfulness factor scores. The scores for FI2, with loadings on "fast," "flexible," and "confident," were characterized as efficiency factor. Factor FI3, with high loadings from "clever" and "critical," was labeled discernment factor. The final factor, FI4, was more difficult to characterize, having positive loadings from "knowledgeable," "flexible," and "critical," but negative loadings from "tough" and "fast." After discussion the factor was interpreted as dealing with theoretical knowledge, and was regarded as expressing a rather academic approach to the forecaster's job.

Analysis 9: "Best-Subset Regression" Predictors of Relative Estimate Size

The sequence of analyses reported here was carried out using the program BMDP9R [8], a multiple regression routine which identifies the "best" subset of predictor variables (defined as the subset for which Mallows' CP statistic is minimized). This procedure was applied successively to each array of factor scores described above, with relative estimate size (factor FG1) as the dependent variable in each case, as follows:

TABLE VIII
VARIMAX FACTOR ANALYSIS OF MEAN RATINGS OF OWN PERSONALITY ON 16 BIPOLAR TRAITS, ACCOUNTING FOR 63% OF THE TOTAL VARIANCE (LOADINGS > 0.30 ARE SHOWN)

	FH1	FH2	FH3	FH4	FH5	FH6
Secure	0.73					
Venturesome	0.73					
Outgoing	0.53		-0.39			
Conscientious		0.71				0.34
Tender-minded	-0.35	0.69				
Trusting		0.63				
Accommodating	-0.49	0.56				
Emotional			0.77			
Tense			0.77			
Practical				0.87		
Forthright				0.75		
Traditional				0.35	0.73	
Self-sufficient			0.42	-0.35	0.62	
More intelligent					0.57	
Serious						0.87
Controlled						0.56
Eigenvalues	*2.00*	*1.84*	*1.74*	*1.68*	*1.45*	*1.44*

1) Relative estimate size was first regressed on the pool of recent experience factor scores (FA1 to FA5) obtained in Analysis 1. The best subset was FA4 alone (residential experience), but this was non-significant ($R = 0.1364$; $F= 1.29$; df = 1.68; $p > 0.05$). It was concluded that there was no systematic relationship between relative size of estimate and recent experience.
2) The same dependent variable was now regressed on the subjective expertise factor scores (FB1 to FB5) obtained in Analysis 2. The best subset consisted of FB1 (commercial expertise) and FB2 (industrial expertise), accounting for 14% of the variance ($R = 0.3750$; $F = 5.56$; df = 2, 68; $p < 0.01$). The beta coefficients for FB1 and FB2 were 0.200 and -0.315 respectively, indicating that scores showing high commercial expertise were generally associated with high relative forecasts, and scores showing high industrial expertise with low relative forecasts.
3) FG1 was then regressed on the factor scores for rated importance of forecaster characteristics (FC1 to FC7)

derived from Analysis 3. The best subset included FC3 (training), FC4 (attribution), and FC7 (experience), accounting for 10% of the variance (R = 0.3157; F = 2.77; df = 3, 75;p< 0.05). The beta coefficients were all positive (0.197, 0.195 for FC3, FC4 and FC7 respectively), suggesting that scores showing a tendency to rate training, attribution, or experience as important characteristics for a forecaster were associated with high relative forecasts.

4) Regression on the factor scores for rated yield general importance of task elements (FD1 to FD5) yielded no significant effects. FG1 was therefore regressed on the alternative set of factor scores given by the task-specific importance ratings (FE1 to FE14) also obtained in Analysis 4. The best subset here consisted of FE6 (the client) and FE8 (cost limits), and accounted for 9.7% of the variance (R = 0.3120; F = 3.88; df = 2, 72;p< 0.05). The beta coefficient for FE8 was negative (-0.204), indicating that scores showing higher ratings of cost limits importance were associated with lower relative forecasts.
5) FG1 was then regressed on the scores derived from the subjects' own personality ratings (FH1 to FH6) obtained in Analysis 7. The best subset consisted of FH6 alone (self-discipline), accounting for 6.3% of the variance (R = 0.2507; F = 5.17; df = 1, 77; p< 0.05). Not surprisingly, the beta coefficient was negative (-0.251), indicating that subjects whose scores showed that they rated themselves as highly self-disciplined were also those who tended to give lower relative forecasts.
6) FG1 was then regressed on the set of scores derived from the trait importance ratings for an ideal forecaster (FI1 to FI4) derived from Analysis 8. The best subset combined FI2 (efficiency) and FI3 (discernment), and accounted for 8.2% of the variance (R = 0.2869; F = 3.45; df = 2, 77; p< 0.05). Both beta coefficients were positive (0.189 and 0.216 respectively), showing that the subjects who rated efficiency and discernment as being very important characteristics of an ideal forecaster were also those who made high relative forecasts.
7) The variables which appeared in the various best subsets were then pooled,and the multiple regression of FG1 on FB1, FB2, FC3, FC4, FC7, FE6, FE8, FH6, FI2, and FI3 was carried out. The program BMDP1R was used first, to compute the proportion of the variance in FG1 accounted for by the pool as a whole. The squared multiple correlation was found to be 0.3055, which was significant (F = 2.414; df = 10, 55; p< 0.02). The analysis was then repeated, using the program BMDP2R to adopt a stepwise procedure. Three of the eight independent variables were retained in the final equation, namely FB2 (industrial expertise), FC7 (experience), and FH6 (discipline), thus accounting for 20% of the variance (R = 0.4468; F = 5.16; df = 3, 62;p< 0.01). It was therefore concluded that the relative size of the subjects' forecasts was significantly predicted by a weighted combination of i) the amount of self-attributed expertise in industrial contracts, ii) the extent to which experience is regarded as an important factor in forecasting, and iii) the amount of self-attributed discipline (see Table X).

TABLE IX
MEAN AND VARIMAX FACTOR ANALYSIS OF RATED IMPORTANCE OF 10 PERSONALITY TRAITS FOR AN IDEAL FORECASTER, ACCOUNTING FOR 62% OF THE TOTAL VARIANCE (LOADINGS > 0.30 ARE SHOWN)

	Mean	SD	FI1	FI2	FI3	FI4
Co-operative	4.99	1.80	0.80			
Careful	6.00	0.98	0.75			
Pleasant	3.63	1.95	0.71			
Fast	5.11	1.23		0.76		-0.32
Flexible	5.61	1.22		0.69		0.36
Confident	6.02	1.01		0.64		
Clever	4.54	1.34			0.79	
Critical	5.60	1.08			0.73	0.32
Knowledgeable	6.39	0.78				0.74
Tough	3.89	1.64		0.32	0.36	-0.51
Eigenvalues			*1.99*	*1.63*	*1.41*	*1.22*

TABLE X
SUMMARY OF STEPWISE REGRESSION OF RELATIVE SIZE OF ESTIMATE ON THE POOLED SUBSET OF PREDICTOR FACTOR SCORES (ORIGINAL VARIABLES HAVING HIGH LOADINGS ON THE FACTORS ARE SHOWN)

Variables	Load	Factor characterisation	Beta
Factories	0.91	Industrial expertise	-0.330
Warehouses	0.90		
Time in prof	0.90	Experience important	0.290
Serious	0.87	Self-rated discipline	-0.242
Controlled	0.56		

Analysis 10: "Best-Subset" Predictors of Estimate Typicality

Since the relative estimate sizes consisted of factor scores generated from five original variables, their mean was zero and their standard deviation 1. The median score, however, was -0.1565, with a semi-interquartile range of 0.6190. Since the distribution was clearly skewed by the existence of a few high forecasters, the median was taken as the preferred measure of centrality, and hence proximity to the median was selected as an index of estimate typicality. An appropriate transformation was applied to the relative estimate sizes as follows:

$$ABS(ABS(FG1 + 0.1565) - K)$$

where K is the sum of the largest score and 0.1565. This transformation gave a value of 0 to the score farthest from the median, and a value of 4.1355 to any score failing exactly on the median.

The procedures outlined in Analysis 9 were repeated on this new dependent variable.

1) As in Analysis 9, relative estimate typicality was first regressed on the pool of recent experience factor scores (FA1 to FA5) obtained in Analysis 1. The best subset consisted of FA1 (commercial experience) and FA2 (public service experience), which together accounted for 9.3% of the variance (R =0.3044; $\underline{F}$ = 3.42; df = 2, 67; p< 0.05). Both beta coefficients were positive (0.195 and 0.235 respectively). These results indicated that subjects having high scores on these two dimensions of recent experience also tended to be closer to the median relative estimate score for the group as a whole.

2) Relative estimate typicality was now regressed on the subjective expertise factor scores (FB1 to FB5) obtained in Analysis 2. The best subset consisted of FB2 (industrial expertise) and FB3 (educational expertise), accounting for 11.2% of the variance (R = 0.3349; $\underline{F}$ = 4.29; df = 2, 68; p< 0.02). The beta coefficients for FB2 and FB3 were 0.172 and 0.289 respectively, indicating that subjects having high scores on these two dimensions of self-rated expertise also tended to be closer to the median relative estimate score for the group as a whole.
3) Typicality was then regressed on the factor scores for rated importance of forecaster characteristics (FC1 to FC7) derived from Analysis 3. The best subset included FC4 (attribution), and FC7 (experience), but this was nonsignificant, accounting for only 1.6% of the variance (R = 0.1249; $\underline{F}$ = 1.24;df = 2, 76; p < 0.05). The results suggested that there was no systematic relationship between the rated importance of these forecaster characteristics and proximity to the median relative estimate score.
4) Regression on the factor scores for rated general importance of task elements (FD1 to FD5) also yielded no significant effects. As in Analysis 9, therefore, the dependent variable was regressed on the alternative set of factor scores given by the task-specific importance ratings (FE1 to FE14) also obtained in Analysis 4. The best subset here consisted of FE3 (geographical factors) and FE13 (services factors), and accounted for 8.8% of the variance (R = 0.2964; $\underline{F}$ = 3.47; df = 2 p< 0.05). The beta coefficient for FE3 was negative (-0.203), indicating that scores showing high importance ratings for geographical factors were associated with typical relative forecasts. By contrast, the beta coefficient for FE13 was positive (0.219), indicating ratings for services were associated with highly typical relative forecasts.
5) The dependent variable was then regressed on the scores derived from the subjects' own personality ratings (FH1 to FH6) obtained in Analysis 7. There were no significant effects, however, indicating that estimate typicality was not predicted by these judgments.
6) Estimate typicality was then regressed on the set of scores derived from the trait importance ratings for an ideal forecaster (FI1 to FI4) derived from Analysis 8, but no significant results were obtained for this set either. It was concluded that there was no strong relationship between the dependent variable and this particular set of judgments.
7) The variables which appeared in the various best subsets were then pooled, and the multiple regression of typicality on FA1, FA2, FB2, FE3, and FE13 was carried out. The squared multiple correlation with this pool as a whole was found to be 0.2109, which was significant ($\underline{F}$ = 2.41; df = 6, 54; p< 0.05). The use of a stepwise procedure showed that only one of the independent variables was retained in the final equation, namely FB3 (educational expertise), thus accounting for only 9% of the variance (R = 0.3032; $\underline{F}$ =5.97; df = 1, 59; p< 0.05). It was therefore concluded that proximity to the median estimate score was significantly predicted by the amount of self-attributed expertise in educational contracts (see Table XI).

TABLE XI
SUMMARY OF STEPWISE REGRESSION OF RELATIVE ESTIMATE TYPICALITY ON THE POOLED SUBSET OF PREDICTOR SCORES (ORIGINAL VARIABLES HAVING HIGH LOADINGS ON THE FACTOR ARE SHOWN)

Variables	Load	Factor characterisation	Beta
Secondary schools	0.90		
Primary schools	0.85	Educational expertise	0.303
Other educational	0.57		

IV. SUMMARY AND CONCLUSIONS

The main findings of the study were as follows:

1) Current expertise in estimating the value of the lowest bid for all types of building projects is a function of the amount of recent experience (last five years) of projects of that particular type, with a smaller but significant contribution to current expertise from the extent of their experience with such tasks in the early stages of their professional careers. Of course their memory of the number of jobs of each or any type undertaken during the different time periods may be fallacious, and their forecasts of their current expertise might be quite mistaken; but within the bounds of these caveats this is a strong finding even should it prove to be solely a psychological finding concerning forecasters beliefs and unrelated to any objective measure of their "expertise." While experience may be diverse, expertise is perceived to be tightly bounded. Thus, for example, while a forecaster may be called upon to produce forecasts for both educational and sociomedical building contracts, experience at the one does not enhance performance at the other. This suggests substantial differences in the processes of forecasting of different generic types of building contract.
2) Although rating themselves in general as Controlled, Calm, Intelligent, Conscientious, Self-sufficient, Traditional, and Shrewd, respondents' rated Knowledgeable, Confident, and Careful as most important and Tough and Pleasant as the least important characteristics of an ideal expert forecaster. The most highly rated personal characteristics that contribute to the expertise of any forecaster were differential perception (the ability to identify important aspects of the contract), sensitivity (awareness of client's requirements), and attitude to uncertainty (coping with insufficient information). The lowest rating was given to differences in character between forecasters (personality factors). In general, judgment and uncertainty were rated above precision, logic, and memory for detail with character differences running last.
3) The most highly rated task elements were complexity, services, and market conditions, with BCIS files rated the lowest. Differences in the relative contribution to success of the different task elements were found from type to type. Thus, for example, while "complexity" has

the highest overall rating across types it did not figure top of the list for any individual job type. This tends to corroborate the finding that expertise tends not to generalize across generic contract types.

4) Forecasts with cost planning were perceived to be more accurate (e.g., "in general" within about 7%) than forecasts without cost planning ("in general" within about 12%), and this difference held across all contract types. In addition, there were differences in the anticipated accuracy of different contract types which held irrespective of the presence of cost planning. Thus our respondents saw cost planning as introducing a fairly uniform improvement in forecasting accuracy.

5) The coefficient of variation of the ball-park estimates (the ratio between standard deviation and mean) was 20.52% averaged across job types, a figure which is similar to previous work in the field and thereby lends some credence to the veridicality of the task. The coefficient of variation varied across contract types with Unit factories and Offices the highest and Sheltered housing substantially lower than the others, indicating the contract types which yielded, respectively, the least and the greatest consensus among ourrespondents. The mean signed differences for all five contract types were underestimates (Table VI), averaging across contract types at around -8%, with the inaccuracy being least for Sheltered housing (-6%) and greatest for Offices (-16%). The modulus differences (ignoring direction of difference) averaged out across contract types at around 17%, with the discrepancy again being the least for Sheltered housing (11%) and the greatest in the case of Offices (22%). As these figures suggest, the distribution of responses for all contract types was skewed, with the majority of responses being underestimates, but the mean underestimate being smaller than the mean overestimate. The most important factors affecting the accuracy of "ball-park" forecasts estimates were found to be a) recent experience, b) current expertise, c) personal characteristics contributing to expertise—especially "training," "attribution" and "length of service" (all overestimates), d) the task elements of "client" (overestimates) and "cost limits" (underestimates), e) the personality factor of "self-discipline" (underestimates), f) the ideal forecaster characteristics of "efficiency" and "discernment" (both overestimates). A tendency toward underestimation National average prices is associated with self-rated current expertise on industrial contracts, with a high relative rating for the importance of cost limits among task factors and a score that is a high relative to the rest of the sample on the self-discipline aspects (serious, controlled) of one's own personality. Two of these three may clearly be regarded as "person factors" and, indeed, all three are subjective expressions of opinion. Conversely, a tendency toward overestimation is associated with self-rated current expertise in commercial contracts, with the view that pre- and post-qualification training, attribution of expertise by self and others, and time served in the profession are important contributors to expertise in forecasting, with a high relative rating for the importance of the client among the set of task factors, and with ratings that are high relative to the rest of the sample for the importance of efficiency and discernment in the makeup of an ideal forecaster. Again, all are subjective matters and testify to the importance of "person factors" in variations in estimations. The single best predictive combination was found to be industrial expertise, length of service, and self-discipline. Again the first and third were associated with a tendency toward underestimations and the second with a tendency toward overestimation. Again all are subjective factors, and the only objective measure in the array—amount of recent experience—made no contribution to the predictability of forecasts.

6) Estimate typicality was most affected by a) recent experience in commercial and public service, with high amounts of recent experience in these two areas tending to produce more typical forecasts (closer to the group median value); b) current expertise, with industrial expertise and educational expertise being both related to more typical forecasts; c) the task elements of "geographical factors" and "services" being associated with atypical and typical forecasts respectively. Thus utilizing this "subjective" measure of estimate accuracy—the consensus among a group of experienced forecasters—a different set of predictors is found giving purchase on variability among respondents. And with this analysis objective differences—in amount of particular kinds of recent contract forecasting experience—do play a part, alongside particular "person factors." After partialing out other effects, the best set of predictors was reduced to the single item rated educational expertise, with high self-ratings on this factor being associated with a tendency to produce typical forecasts, in line with one's peers. The objective measures of recent experience did not contribute to this final equation, again testifying to the important contribution of "person factors" to expertise in forecasting.

This study provides ample evidence of the importance of the human element in building price forecasting. It is shown that expertise is very much of a project-specific nature and does not extend in a simplistic way to projects outside the defined domain. This implies that estimators must exercise of great caution when undertaking work even slightly outside their regular activities. "Knowledge" and "care" are the key-words for good estimating. Different building types demand different emphasis and special attention needs to made on the complexity of the project, the degree of services content, and particular sub-market conditions. The easiest projects appear to be industrial (factories) and residential (houses) with offices being the hardest, probably due to the wider variety of design and quality options in the latter. Again this suggests the need for greater caution when wide design options are available by, for example, delaying estimates until more basic design decisions are made.

The study also serves to dispel a few myths that have arisen over the years. Geographical location, for instance, was found not to be a major issue. Similarly, there is no evidence of any "X" factor whereby individuals can claim any mystical inborn talent. From our work to date, it is clear that good estimators have exactly the same attributes as good gamblers—they do their research selectively and thoroughly, think carefully, and concentrate on what they know best.

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REFERENCES

[1] D. T. Beeston, "One statistician's view of estimating," *Cost Study 3*, Building Cost Information Service, Royal Institution of Chartered Surveyors, July 1974.

[2] Building Cost Information Service, 1987, Section AA Briefing, Section KB Studies of Average Building Prices, nos. 245, 251, 263, and 273, Royal Institution of Chartered Surveyors.

[3] B. C. Jupp and V. McMillan, "The reliability of cost data," contribution to conference held at the Polytechnic of the South Bank, London, June 1981.

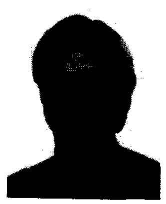
[4] N. Morrison and S. Stevens, "Construction cost data base," 2nd annual report of research project by Department of Construction Management, University of Reading, for Property Services Agency, Directorate of Quantity Surveying Services, DOE, 1980.

[5] R. M. Skitmore, "The influence of professional expertise in construction price forecasts," Dept. Civil Engineering, Univ. of Salford, ISBN 0901025 09 7, 1985.

[6] R. M. Skitmore, S. G. Stradling, A. Tuohy, and H. Mkwezalamba, "The accuracy of construction price forecasts: A study of quantity surveyors' performance," Dept. Civil Engineering, Univ. of Salford, ISBN 0 901025 12 7, 1990.

[7] R. Roberts, K. J. Harper, S. G. Stradling, and F. M. Quinn, "Being discrete on the beat," *Police Review*, pp. 1732–1733, Aug. 19, 1988.

[8] *BMDP-79: Biomedical Computer Programs (P-Series)*, W. J. Dixon and M. B. Brown, eds. Berkeley, CA: Univ. of California Press, 1979.



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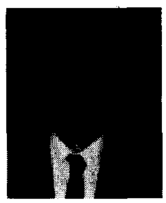

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